chaos. We also demonstrate that the second order Renyi entropy of the plankton biomass fluctuations can be considerably greater than the values of the dominant Lyapunov exponents. It implies that the qualitative description of the chaotic plankton dynamics in the Naroch Lakes requires a four- or higher dimensional phase space. In other words, interspecific interactions across trophic levels (for example between fish, zooplankton, phytoplankton and bacterioplankton) can significantly contribute to the emergence of chaos far away from the edge of chaos.

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Работа выполнена при частичной поддержке РФФИ (грант 16-31-00403 мол_а)

USING THE ARTIFICIAL NEURAL NETWORK (ANN) MODEL TO PREDICT HARMFUL ALGAL BLOOM (HAB) DEVELOPMENT

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In many watercourses around the world including in the United States and Canada, harmful algae including blue-green algae (or cyanobacteria) wererecently blooming and surprisingly increasing at a large scale without any good understanding or explanation about their causes and effects. The algal growth has been normally explained by relationships between nutrient levels, water temperature, and other physical conditions such as light intensity, wind effects and flow circulation. An optimal combination of all these factors could lead to a blooming pattern and a large scale proliferation of harmful algal species.

Field experiments are extremely necessary to elucidate various factors that affect algal blooms and their proliferation. However, factors that can be determined in field experiments are limited, costly and time consuming. Moreover, these factors cannot represent their combining effects on the algal growth. Therefore, we would use the mathematical approach to deal with the coupling effects of governing parameters in the bloom occurrence and proliferation. We determine the key factors which govern the algal dynamics and establish an algal response model which can effectively simulate the timing and magnitude of algal blooms.

The mathematical approach we used is the Artificial Neural Network (ANN) to model the nonlinear relationships between environmental factors and algal blooms in Mattatal Lake *(ML, Canada)*. Inspired by the biological nervous system and artificial intelligence (McCulloch and Pitts, 1943), the ANN applied in our simulation consists of a large number of simple processing elements that are variously called neurons or nodes. Each neuron (node) is connected to other nodes by means of direct communication links, each with an associated weight function. These functions represent information being used the net to solve the problem. We suggest the back-propagation multi-layer neural network, including three layers: input layer (Data observations), hidden layer(s) (intermediate nodes) and output layer (conclusions). Good input can substantially improve model performance.

Our study is based on a set of five main parameters for the input sets: 1) Total Phosphorus (TP); 2) Nitrates; 3) Dissolved Oxygen (DO); 4) Water temperature; and 5) pH. The only output *Y*in this first step model is the quantity of Chlorophyll-a, representing the growth of algae. Five input nodes represented by variables $X_i=1$ *to* 5 stand for these five main parameters. The design of this experiment used random sampling to cover all equation surfaces. Data collected in two years will be summarized in the input table and will be used to design the ANN model. In fact, we did use a data set with more than hundred points to train and validate the model. The below table is an example showing different values among dataset under the form of inputs/output we used for our simulation by ANN.

Table. Example of input and output datausedin the ANN model

Inputs X_1 to X_5					Output
Total phosphorus (mg/l)	**Nitrate + Nitrite (mg/l)**	**pH**	**DO (mg/l)**	**Temperature (C^0)**	**Chlorophyll-a (µg/l)**
0,858	0.26	7.18	10.39	17.47	1.60
0,066	0.16	7.18	10.38	17.42	1.56
…	…	…	…	…	…
0,198	0.44	7.15	10.97	17.40	3.11

In this research, we present some preliminary predictive results of the mathematical simulation based on data we obtained from two years 2015–2016 on ML. The simulation resultsshow that when TP is increased, the concentration of Chlorophyll-a slowly increases. For example once the value of TP surpasses 0.25 mg/l, the concentration of Chlorophyll-a increases fairly sharply. Once the TP value is over 0.7 mg/l, the Chlorophyll-a value plateaus at 90 μg/l. Nitrates do not have as fast an effect on the Chlorophyll-a as TP does. The concentration of Chlorophyll-a increases slowly until the value of Nitrate is 0.6 mg/l. At this point, the value of Chlorophyll-a increases at a steeper slope until Nitrate reaches 1.6 mg/l. If the temperature goes beyond 30 °C, the Chlorophyll-a decreases and tends to zero when temperature reaching 35°C. When the temperature decreases to the low values less than 11°C, there is a sharp decrease in the value of Chlorophyll-a. As the value of DO is increased, the Chlorophyll-a concentration slowly decreases. Once the value of DO surpasses 8 mg/l, Chlorophyll-a starts to increase with DO. When the pH value exceeds 7, the Chlorophyll-a concentration sharply increases. This increase stopped once the pH reaches the value of 9, and once that value is exceeded, the Chlorophyll-a concentration slightly decreases to a plateau of 80 μg/l. As both TP and DO are increased, the concentration of Chlorophyll-a increases as well.

We can conclude that mathematical models therefore have many advantages for studying coupled effects with parameters that are more realistic: nutrients, light and temperature. Acquiring sufficient data is as important in both developing predictive models as well as making accurate predictions. Microalgae dynamics modelling is considered an effective tool for complementing the limitations of field and laboratory experiments, and is an approach that can be used at a minimal cost. However, we need to continue more sampling next several years for a complete database of ML as well as to build other independent databases in other lakes for the good external validations of the model, and for a more advanced model of the prediction and prevention of HAB problem.